

AN EMPIRICAL SURVEY OF FRONTIER EFFICIENCY MEASUREMENT TECHNIQUES IN HEALTHCARE SERVICES

ANDREW WORTHINGTON*

School of Economics and Finance, Queensland University of Technology, Australia

SUMMARY

Healthcare institutions worldwide are increasingly the subject of analyses aimed at defining, measuring and improving organisational efficiency. However, despite the importance of efficiency measurement in healthcare services, it is only relatively recently that the more advanced econometric and mathematical frontier techniques have been applied to hospitals, nursing homes, health management organisations and physician practices. This paper attempts to provide a synoptic survey of the comparatively few empirical analyses of frontier efficiency measurement in healthcare services. Both the measurement of inefficiency in healthcare services and the determinants of healthcare efficiency are examined.

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INTRODUCTION

Healthcare costs in most developed economies have grown dramatically over the last few decades and it is widely believed that the inefficiency of healthcare institutions, at least in part, has contributed. In response to this belief, an extensive body of literature has addressed the empirical measurement of efficiency in healthcare institutions around the world. And while hospitals have been the subject of most of these efficiency studies to date, the efficiency of other healthcare institutions has also been addressed. These include nursing homes, health maintenance organisations, physician practices, and district health authorities. Nevertheless, these studies share a common focus; namely, the growing volume of healthcare costs, the effect of these costs on public expenditure and private industry, and the impact of increased competition in the healthcare market.

* Correspondence to: Andrew Worthington, School of Economics and Finance, Queensland University of Technology, GPO Box 2434, Brisbane, QLD 4001, Australia. Tel. 61 7 3864 2658, Fax. 61 7 3864 1500, email. a.worthington@qut.edu.au

However, in contrast to the empirical work undertaken in other service-based industries, particularly finance and education, relatively little attention has been paid by health economists to the full exploration of other standard techniques of economics for assessing efficiency. More particularly, the primary tools of efficiency measurement in healthcare services to date have hitherto been the application of cost-benefit, cost-effectiveness and simple cost function analyses [see, for example, Gertler (1989), Gertler and Waldman (1992) and Parkin and Hollingsworth 1997)]. Indeed, it is only relatively recently that attempts have been made to apply the more advanced econometric and mathematical frontier techniques to the efficiency of institutions in the provision of healthcare services. The present paper attempts to review the evolving empirical literature in question within a common theoretical framework.

The paper itself is divided into four main areas. The first section briefly discusses the theoretical basis of frontier efficiency measurement techniques. The second section examines the literature in the empirical measurement of inefficiency in healthcare services. The third section discusses the purported determinants of healthcare service efficiency. The paper ends with some brief concluding remarks.

THE THEORY OF MICROECONOMIC EFFICIENCY MEASUREMENT

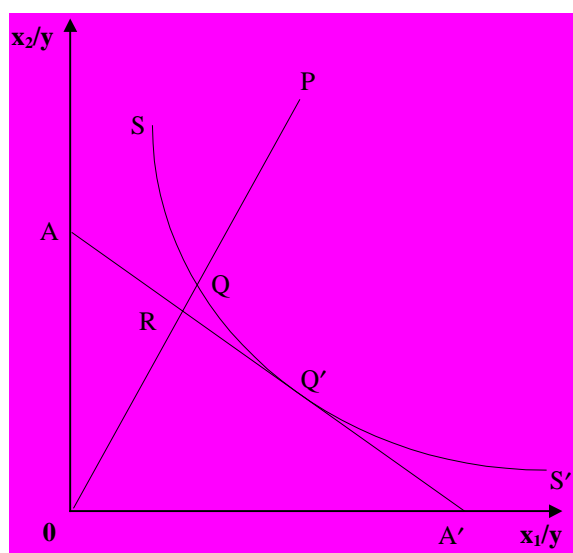
Economists have developed three main measures of efficiency. Firstly, *technical efficiency* refers to the use of productive resources in the most technologically efficient manner. Put differently, technical efficiency implies the maximum possible output from a given set of inputs. Within the context of healthcare services, technical efficiency may then refer to the physical relationship between the resources used (say, capital, labour and equipment) and some health outcome. These health outcomes may either be defined in terms of intermediate outputs (number of patients treated, patient-days, waiting time, etc.) or a final health outcome (lower mortality rates, longer life expectancy, etc.) (Palmer and Torgenson 1999). Secondly, *allocative efficiency* reflects the ability of an organisation to use these inputs in optimal proportions, given their respective prices and the production technology. In other words, allocative efficiency is concerned with choosing between the different technically efficient combinations of inputs used to produce the maximum possible outputs. Palmer and Torgenson (1999: 1136) illustrate healthcare-related allocative efficiency as follows:

Consider, for example, a policy of changing from maternal age screening to biochemical screening for Down's syndrome. Biochemical screening uses fewer amniocenteses but it requires the use of another resource – biochemical testing. Since different combinations of inputs are being used, the choice between interventions is based on the relative costs of these different inputs.

Finally, and when taken together, allocative efficiency and technical efficiency determine the degree of *productive efficiency* (also known as total economic efficiency). Thus, if an organisation uses its resources completely allocatively and technically efficiently, then it can be said to have achieved total economic efficiency. Alternatively, to the extent that either allocative or technical inefficiency is present, then the organisation will be operating at less than total economic efficiency.

The recent history of microeconomic efficiency measurement begins with Farrell (1957) who defined a simple measure of firm efficiency that could account for multiple inputs within the context of technical, allocative and productive efficiency. In this approach, Farrell (1957) proposed that the efficiency of any given firm consisted of two components: technical efficiency, or the ability of a firm to maximise output from a given set of inputs, and allocative efficiency, or the ability of a firm to use these inputs in optimal proportions, given the respective prices. Combining the two measures provides the measure of productive efficiency.

Figure 1. Technical, allocative and total efficiency



In parenthesis for technically inclined readers, Farrell's (1957) argument is contained in Figure 1. Here two inputs, x_1 and x_2 , are utilised to produce a single output y , so that the production frontier is $y = f(x_1, x_2)$. If we assume constant returns to scale (where the

relationship between output y and inputs x_1 and x_2 does not change as the inputs increase), then $1 = f(x_1/y, x_2/y)$. The isoquant (showing the alternative combinations of inputs which can be used to produce a given level of output) of the fully efficient firm SS' permits the measurement of technical efficiency. Now, for a given organisation using quantities of inputs (x_1^*, x_2^*) defined by point $P(x_1^*/y, x_2^*/y)$ to produce a unit of output y^* , the level of technical efficiency, or the ability of an organisation to maximise output from a given set of inputs, may be defined as the ratio OQ/OP . This ratio measures the proportion of (x_1, x_2) actually necessary to produce y^* . Thus $1 - OQ/OP$, the technical inefficiency of the organisation, measures the proportion by which (x_1^*, x_2^*) could be reduced (holding the input ratio x_1/x_2 constant) without reducing output. It accordingly measures the possible reduction in the cost of producing y^* . Furthermore, given constant returns to scale, it also roughly estimates the proportion by which output could be increased, holding (x_1^*, x_2^*) constant. Point Q , on the other hand, is technically efficient since it already lies on the efficient isoquant (note that $OQ/OQ = 1$).

If the input price ratio AA' is known (showing the different combinations of inputs that can be purchased with a given cost outlay), then allocative efficiency [referred to by Farrell as price efficiency] can be calculated. The ability of an organisation to use the inputs in optimal proportions, given the respective prices at point P , is the ratio OR/OQ , and correspondingly the allocative inefficiency is $1 - OR/OQ$. The distance RQ is the reduction in production costs which would occur if production occurred at Q' – the allocatively and technically efficient point, rather than Q – the technically efficient, but allocatively inefficient point. Hence, total economic or productive efficiency [referred to by Farrell as overall efficiency] is the ratio OR/OP , and total inefficiency is therefore $1 - OR/OP$. The cost reduction achievable is the distance RP which is obtained from moving from P (the observed point) to Q' (the cost minimising point).

Of course, these efficiency measures assume the production function of the fully efficient firm is known. As this is usually not the case, the efficient isoquant must be estimated using sample data. Farrell (1957) suggested the use of either: (i) a nonparametric piecewise-linear convex isoquant constructed such that no observed point should lie to the left or below it (known as the *mathematical programming* approach to the construction of frontiers); or (ii) a parametric function, such as the Cobb-Douglas form, fitted to the data, again such that no observed point should lie to the left or below it (known as the *econometric* approach). These approaches use different techniques to envelop the observed data, and therefore make

different accommodations for random noise and for flexibility in the structure of the production technology.

First, the econometric approach specifies a production function and normally recognises that deviation away from this given technology (as measured by the error term) is composed of two parts, one representing randomness (or statistical noise) and the other inefficiency. The usual assumption with the two-component error structure is that the inefficiencies follow an asymmetric half-normal distribution and the random errors are normally distributed. The random error term is generally thought to encompass all events outside the control of the organisation, including both uncontrollable factors directly concerned with the ‘actual’ production function (such as differences in operating environments) and econometric errors (such as misspecification of the production function and measurement error). This type of reasoning has primarily led to the development of the ‘stochastic frontier approach’ which seeks to take these external factors into account when estimating the efficiency of real-world organisations, and the earlier ‘deterministic frontier approach’ which assumes that all deviations from the estimated frontier represent inefficiency. A number of studies have used these approaches to estimate the efficiency of healthcare institutions. These include Wagstaff (1989), Hofler and Rungeling (1994), Zuckerman *et al.* (1994), Defelice and Bradford (1997), Chirikos (1998) and Gerdtham *et al.* (1999).

Second, and in contrast to the econometric approaches which attempt to determine the *absolute* economic efficiency of organisations against some imposed benchmark, the mathematical programming approach seeks to evaluate the efficiency of an organisation *relative* to other organisations in the same industry. The most commonly employed version of this approach is a linear programming tool referred to as ‘data envelopment analysis’ (DEA). DEA essentially calculates the economic efficiency of a given organisation relative to the performance of other organisations producing the same good or service, rather than against an idealised standard of performance. A less-constrained alternative to DEA sometimes employed in the analysis of efficiency (though presently unapplied to healthcare) is known as ‘free-disposal hull’. Both DEA and FDH are nonstochastic methods in that they assume all deviations from the frontier are the result of inefficiency. Banker, Conrad and Strauss (1986), Fazel and Nunnikhoven (1992), Kooreman (1994), Parkin and Hollingsworth (1997) and Burgess and Wilson (1998) have applied these approaches to healthcare institutions. Applications that use Malmquist productivity indexes (as derived from DEA-like linear programs) to measure changes in efficiency and productivity over time are also found in the healthcare literature. These include Fare *et al.* (1993) and Linna (1998) [more detailed

theoretical introductions to frontier efficiency measurement techniques may be found in Fried, Lovell and Schmidt (1993), Charnes, Cooper, Lewin and Seiford (1995) and Coelli, Rao and Battese (1998)].

The discussion thus far has addressed three separate, though conceptually similar, theoretical approaches to the assessment of productive efficiency. These are the deterministic frontier approach, the stochastic frontier approach, and the mathematical programming approach. Whilst the selection of any particular approach is likely to be subject to both theoretical and empirical considerations, it may be useful to summarise the strengths and weaknesses of each technique. The emphasis here is not on selecting a superior theoretical approach, as it should be emphasised that the mathematical programming and econometric approaches address different questions, serve different purposes and have different informational requirements.

The first approach examined was the construct of the deterministic statistical frontier [see, for example, Wagstaff (1989)]. Using statistical techniques a deterministic frontier is derived, such that all deviations from this frontier are assumed to be the result of inefficiency. That is, no allowance is made for noise or measurement error. In the primal (production) form, the ability to incorporate multiple outputs is difficult, whilst using the dual cost frontier, such extensions are possible. However, if the cost frontier approach is employed, it is not possible to decompose inefficiency into allocative or technical components, and therefore all deviations are attributed to overall cost inefficiency.

In terms of computational procedure, the deterministic frontier approach necessitates a large sample size for statistical reasons. In addition, it is generally regarded as a disadvantage that the distribution of the technical inefficiency has to be specified, ie. half-normal, normal, exponential, log-normal, etc. Ideally this would be based on knowledge of the economic forces that generate such inefficiency, though in practice this may not be feasible. If there are no strong *a priori* arguments for a particular distribution, a choice is normally made on the basis of analytical tractability. Similarly, the choice of a particular technology is imposed on the sample, and once again this may be a matter of empirical convenience (ie. Cobb-Douglas, translog, etc). Moreover, the choice of a particular production function may place severe restrictions on the types of analysis possible, and therefore the content of policy prescriptions, using this particular approach.

The second approach discussed, namely the stochastic frontier, removes some of the limitations of the deterministic frontier [see, for example, Wagstaff (1989), Zuckerman *et al.* (1994), Gonzalez Lopez-Valcarcel and Barber and Perez (1996) and Linna (1998)]. Its biggest

advantage lies in the fact that it introduces a disturbance term representing noise, measurement error, and exogenous shocks beyond the control of the production unit. This in turn permits the decomposition of deviations from the efficient frontier into two components, inefficiency and noise. However, in common with the deterministic approach, an assumption regarding the distribution (usually normal) of this noise must be made along with those required for the inefficiency term and the production technology. The main effect here is that under both approaches, especially the stochastic frontier, considerable structure is imposed upon the data from stringent parametric form and distributional assumptions. In addition, stochastic frontier estimation uses information on prices and costs, in addition to quantities, which may introduce additional measurement errors.

The final programming approach differs from both statistical frontier approaches in that is fundamentally nonparametric, and from the stochastic frontier approach in that is nonstochastic [see, for example, Grosskopf and Valdmanis (1987), Byrnes and Valdmanis (1993), Kooreman (1994a), Thanassoulis *et al.* (1996) and Puig-Jonoy (1998)]. Thus, no (direct) accommodation is made for the types of bias resulting from environmental heterogeneity, external shocks, measurement error and omitted variables. Consequently, the entire deviation from the frontier is assessed as being the result of inefficiency. This may lead to either an under or over-statement of the level of inefficiency, and as a nonstochastic technique there is no possible way in which probability statements of the shape and placement of this frontier can be made. In view of erroneous or misleading data, some critics of DEA have questioned the validity and stability of measures of DEA efficiency.

However, there are a number of benefits implicit in the programming approach that makes it attractive on a theoretical level. Given its nonparametric basis, substantial freedom is given on the specification of inputs and outputs, the formulation of the production correspondence relating inputs to outputs, and so on. Thus, in cases where the usual axioms of production activity breakdown (ie. profit maximisation) then the programming approach may offer useful insights into the efficiency of these types of industries [some assumptions regarding the production technology are still made regardless, such as that relating to convexity]. Similarly, it is entirely possible that the types of data necessary for the statistical approaches are neither available nor desirable, and therefore the imposition of as few as possible restrictions on the data is likely to be most attractive. Simulation studies [see, for instance, Banker, Charnes, Cooper and Maindiratta (1988)] have also indicated that the piecewise linear production frontier formulated by DEA is generally more flexible in approximating the true production frontier than even the most flexible parametric function form.

These theoretical and empirical considerations explain part of the dominance of DEA in healthcare efficiency measurement studies. The obvious desirability of quantifying inputs and outputs in different units of measurement is one consideration. For example, many healthcare studies define inputs as the number of physicians, nursing and ancillary staff along with non-labour inputs in dollar terms, especially plant and equipment assets [see, for instance, Grosskopf and Valdmanis (1987), Valdmanis (1992) and Parkin and Hollingsworth (1997)]. Alternatively, outputs are often defined as the number of patient days, surgeries or discharges, along with indexes of casemix categories and the percentage of cases using certain equipment [examples include Wagstaff (1989) and Gonzalez Lopez-Valcarcel and Barber Perez (1996)]. Likewise the difficulty in defining input costs in many public sector contexts may account for the emphasis of healthcare efficiency studies on measuring technical efficiency alone [see, for example, Chattopadhyay and Ray (1996), Puig-Jonoy (1998) and Burgess and Wilson (1998)]. Finally, and once again in a public sector context where the usual axioms of production activity breakdown, there is the ability to define inputs and outputs depending on the conceptualisation of healthcare performance thought most appropriate.

MEASURING INEFFICIENCY IN HEALTHCARE

Within the broad scope of healthcare services, frontier efficiency measurement techniques have been applied to many different types of institutions. As detailed in Table 1, these include hospitals (Banker, Conrad and Strauss 1986; Ley 1991; Fare *et al.* 1993; Chirikos 1998), physician practices (Chillingerian 1993; Defelice and Bradford 1997), nursing homes (Hofler and Rungeling 1994; Chattopadhyay and Ray 1996) and substance abuse clinics (Alexander *et al.* 1998). And while the literature has been predominantly concerned with the efficiency of North American institutions, applications in Spain (Wagstaff 1989; Ley 1991), Scandinavia (Fare *et al.* 1993; Luoma *et al.* 1996; Mobley and Magnussen 1998), Taiwan (Lo *et al.* 1996) and the United Kingdom (Thanassoulis *et al.* 1996; Parkin and Hollingsworth 1997) have also been made. As indicated, the primary frontier technique employed in assaying the efficiency of healthcare services has been the data envelopment analysis or DEA approach (Fizel and Nunnikhoven 1992; Valdmanis 1992; Kooreman 1994; Thanassoulis, Boussofiane and Dyson 1996; Parkin and Hollingsworth 1997).

As early as Banker, Conrad and Strauss (1986), an attempt was made to compare the results of the conventional translog cost function and DEA. Of especial interest in this particular study was the level of similarities or differences between the two approaches in

ascertaining increasing, constant or decreasing returns-to-scale, and estimating marginal rates of output transformation and technical inefficiencies of individual hospitals. Measuring inputs in terms of nursing, ancillary, administrative and general services, and outputs in terms of patient days, Banker, Conrad and Strauss (1986: 38) using a sample of North Carolina hospitals found that DEA was “able to examine the possibility of increasing or decreasing returns to scale prevailing in specific segments of the production possibility set”. More particularly, whereas the translog cost function indicated cost returns-to-scale across the sample, DEA found that the most productive scale size varied dramatically with different output mixes and capacity. Nonetheless, when it came to comparing the efficiency ratings, Banker, Conrad and Strauss (1986) concluded *inter alia* that the two techniques were in broad agreement.

Comparisons between frontier efficiency measurement techniques have also been made. For example, Gonzalez Lopez-Valcarcel and Barber Perez (1996) compared DEA-based technical efficiency measures with stochastic frontier cost efficiency indexes in a sample of Spanish general hospitals, and Linna (1998) examined DEA measures and stochastic frontier estimates of cost efficiency in Finnish acute care hospitals. Both studies concluded that the choice of approach did not significantly influence the results. Further, efforts have also been made in healthcare services to compare frontier techniques and ratio analysis as alternative tools for assessing performance. For example, Thanassoulis, Boussofiane and Dyson (1996) compared U.K. National Health Service (NHS) performance indicators (PI) for perinatal care units with DEA measures of productive performance. They concluded that not only was there no reason why PI values could be routinely accompanied by DEA measures of performance, but that the multiple-input, multiple-output nature of the latter could be used in a straightforward manner to set performance targets. Nunamaker (1983) also compared univariate ratios and DEA, though this time in the form of cost per patient day.

In so far as subsequent empirical research is concerned, the Banker, Conrad and Strauss (1986) study is important, not so much because it compares alternative techniques for efficiency measurement [an issue similarly developed in Wagstaff (1989)], but that it sets an important precedent for the specification of healthcare inputs and outputs. Thus, most subsequent studies [see, for example, Byrnes and Valdmanis (1993), Kooreman (1994) and Parkin and Hollingsworth (1997)] conceptualise healthcare as combining the inputs of labour (normally the number of staff) and capital (often proxied by bed capacity) in order to produce some easily-observed unit of output, such as discharges or inpatient days. For example, Valdmanis (1992) conceptualised Michigan hospitals as managing the inputs of housestaff,

physicians and nurses in order to maximise adult, paediatric and intensive care inpatient days and emergency and ambulatory visits. Alternatively, Thanassoulis, Boussofiane and Dyson (1996) in a study of U.K. district health authorities focused on the obstetrical/gynaecological function and measured output as the number of deliveries, legally-induced abortions and the length of patient stay.

Nevertheless, placing emphasis on the production of inpatient care, because it normally comprises the largest component of hospital costs and can be readily measured, can be called into question on at least three counts. First, as noted by Kooreman (1994a: 305) one of the problems of efficiency analysis of healthcare institutions is that the conceptual output – improved health status, or even more generally, improved quality of life – is difficult, if not impossible, to measure. Recognising these data problems, Chillingierian (1993) argued that defining healthcare output by patient days, or discharges, or even cases, is acceptable so long as adjustment is made first for the mix, or complexity of cases, and second for the intradiagnostic severity of cases. Using a sample of U.S. physicians, Chillingierian (1993) incorporated these concepts by classifying discharges on the basis of either a satisfactory (ie. a healthier state) or unsatisfactory outcome (ie. the presence of morbidity or mortality).

However, the more usual case is to engage in some form of aggregation in order to ensure homogeneous outcomes. For example, Banker, Conrad and Strauss (1986) categorised outputs in terms of patient's age: that is, Medicare patients, paediatric patients and adult patients. Alternatively Grosskopf and Valdmanis (1987) disaggregated outputs by type of treatment: that is, acute in-patient days, intensive care inpatients days and the number of surgeries. Notwithstanding these attempts, Newhouse (1994) argued that case-mix controls by hospital (ordinarily diagnosis-related groups) usually encompass non-random variation. The problem of defining healthcare output is further highlighted when it is realised that even diagnosis-related group outputs, which in turn are aggregated measures, are likely to involve several hundred separate categories. Citing earlier studies, Newhouse (1993) gives the example where patients may be disproportionately admitted to hospitals that are equipped to undertake specific treatments, and accordingly is not the result of variation in efficiency, rather variation in a healthcare institution's patients. This has obvious implications for the validity of efficiency measures. Skinner (1994: 324), for example, argues that "Vitaliano and Toren (1994a; 1994b) and Zuckerman *et al.* (1994) are among the best applications of the stochastic frontier approach in that both carefully specify the underling cost variables, and (more importantly) controlling to the extent possible for both the quality of care provided and the case-mix of patients"

The second problem found with this conceptualisation of healthcare behaviour is that several inputs, most often capital, are typically not measured. For example, Fizel and Nunnikhoven (1992) and Kooreman (1994) measured the efficiency of Michigan and Dutch nursing homes on the basis of labour inputs only. Kooreman (1994: 306) justified this selective input approach on the basis that management typically has control over labour inputs, “but the use of capital inputs is largely beyond their ability to determine”. While omitted inputs may certainly lead to functional misspecification a defence is that the omitted variable (mostly capital) is used in fixed proportions to other inputs. Regardless, even where attempts are made to incorporate non-labour inputs, more commonplace measurement problems may arise. In these instances, capital has been proxied by the number of hospital beds (Byrnes and Valdmanis 1993; Hofler and Rungeling 1994), depreciation and interest expenses per bed (Hadley and Iezzoni 1994), net plant assets (Valdmanis 1992) and the U.K.’s National Health Service capital charge on assets and investments (Parkin and Hollingsworth 1997). Though the most appropriate input measure is the flow of capital services per period, most healthcare studies use a measure of capital stock in its place.

However, variation within the sample may also arise in unmeasured inputs that are likely to have an even greater influence on hypothesised inefficiency. For example, the presence of hospital teaching and research programs further complicates the issue, and has only been addressed by a small number of studies [see, for instance, Wagstaff (1989) and Zuckerman, Hadley and Iezzoni (1994)]. Lastly, the degree of central planning and control found in most national healthcare systems, and regulation governing input prices, also infers that input prices may be more easily discerned than in equivalent contexts, particularly in the case of public hospitals (Fare, Grosskopf, Lindgren and Roos 1993).

The final problem with healthcare studies, namely the difference between ‘public’ and ‘not-for-profit’ or ‘voluntary’ health organisations, and more broadly, the issue of ownership form and efficiency, has generally received more attention in the literature (Grosskopf and Valdmanis 1987; Fizel and Nunnikhoven 1992; Valdmanis 1992; Hofler and Rungeling 1994; Kooreman 1994). In general, it is argued that in the case of not-for-profit entities, the act of ploughing back excess revenues into recurrent expenditure makes them attractive to meeting physician demands for high quality and advanced medical technology, and other hospital substitutes for physician input. Nonetheless, these incentives to behave inefficiently may be off-set by the need to ensure financial viability in order to expand services, especially those that “lose money (ie. research and charity care)” (Valdmanis 1992: 187). Conversely, whilst public hospitals may be relatively inefficient due to the administrative goals of budget-

maximising bureaucrats along the lines envisaged by Niskanen, and hiring excess labour inputs under public hospital employment policy, the governmental budgetary constraints may serve to constrain cost inefficiencies.

A number of studies have addressed these and related issues empirically. Using a sample of U.S. hospitals, both public and not-for-profit, Valdmanis (1992) concluded that DEA rather than cost or profit functions added valuable insights into the production practices of these two ownership forms. Valdmanis (1992: 197) justified ten different model specifications using a selection of nine outputs and inputs on a number of counts:

Given the various possibilities of specifying inputs and outputs, several iterations of the DEA could be applied to answer a policy or management question. However, what needs to be determined is whether minor changes in the specification would fundamentally alter the results.

With reference to the latter, Valdmanis (1992) found that slight alteration in the input and output variables resulted in only small changes to the results, and public hospitals were consistently found to be more efficient than not-for-profit hospitals on the basis of technical efficiency. Conversely, Fazel and Nunnikhoven (1992) using a DEA approach, and later Hofler and Rungeling (1994) and Kooreman (1994) employing an econometric and mathematical programming approach respectively, found that for-profit nursing homes had higher mean levels of efficiency than non-profit homes. Using a property rights framework, Fazel and Nunnikhoven (1992) theorised that since for-profit homes have exclusive rights to income generated, with the resulting incentive to meter input productivity and rewards conscientiously, and given the threat of take-overs, an incentive existed to produce efficiently. On the other hand, in a non-profit home the owner's rights to income are attenuated (and ultimately non-transferrable) and non-pecuniary goods are consumed at the expense of efficiency and wealth. Using DEA frontiers for non-profit and for-profit homes, both separately and pooled, Fazel and Nunnikhoven (1992: 437) concluded that the for-profit isoquant was statistically lower than the non-profit isoquant. Similar results were observed by Hofler and Rungeling (1994) and Kooreman (1994) in studies of U.S and Dutch nursing homes respectively, though in the context of second-stage regressions.

DETERMINANTS OF HEALTHCARE EFFICIENCY

An increasing number of empirical studies have made inroads into examining the determinants of the efficiency of healthcare institutions, particularly nursing homes and hospitals. Apart from the issue of ownership type, factors that are hypothesised to exert an

influence on outcomes may be broadly grouped into (i) size and capacity, (ii) output quality and degree of specialisation, (iii) market structure and funding issues, and (iv) geographic location. Most often frontier-based efficiency scores are grouped and simple analytical techniques are used to compare the distribution of efficiency [see, for instance, Ley (1991), Byrnes and Valdmanis (1993), Chattopadhyay and Ray (1996)]. However, one of the most pervasive analytical tools in data envelopment analysis in particular, and the efficiency literature in general, is the use of a two-step or stage procedure to analyse efficiency scores (see Table 1 for details). The basic idea is that the efficiency scores, whether obtained from an econometric frontier or data envelopment analysis, are treated as the dependent variable in an auxiliary regression. For example, a number of healthcare studies have regressed the predicted inefficiencies on a set of organisational-specific factors, such as the percentage of doctors on staff, the extent of local competition, and dummy variables for teaching, non-profit and for-profit hospitals. This approach is likely to provide valuable insights into the causes of efficiency differentials. However, three problems typically arise.

Firstly, depending on the type of inefficiency score computed, efficiency scores are typically censored. For example, DEA measures of inefficiency are bound by zero and unity, with a large number of observations, depending upon the model specification, found at the upper limit. As a consequence, ordinary least squares estimation is not appropriate and limited dependent variable models are usually called for. The two remaining problems are largely conceptual and closely related. The first is that if the variables employed in the second stage are thought to affect performance, why were they not included in the original model? The reasons for this can often be ascribed either to limitations in the underlying model, such as the inability to incorporate categorical or exogenous variables, or more prosaically, to empirical convenience. However, perhaps the more intractable problem resides in the issue of the distribution of the errors in both steps. That is, if the variables used in specifying the original efficient model are correlated with the explanatory variables used in the second stage, then the second-stage estimates will be inconsistent and biased. Recent theoretical papers have noted this inconsistency and have specified stochastic frontier models in which the inefficiency effects are made an explicit function of firm-specific factors, and all parameters are estimated in a single-stage maximum likelihood procedure. Some of the DEA-related theoretical literature has also examined the effects of differing distributional assumptions. Much work remains to be done.

Returning to the empirical literature, a number of healthcare studies have incorporated a measure of size in the second-stage analysis (Fizel and Nunnikhoven 1992; Kooreman 1994;

Zimmerman, Hadley and Iezzoni 1994). For example, Kooreman (1994) employed both a measure of size (proxied by the number of beds) and the occupancy rate of these beds. In the first instance, Kooreman (1994) argued that since the efficient frontier in his study of Dutch nursing homes exhibited constant returns-to-scale, the size variable would probably be an important explanatory variable. A positive relationship between size and efficiency would be expected to hold. Kooreman (1994: 310) argued that a higher occupancy rate would generally impinge upon the ability of management to attain efficient outcomes, since they were not generally “able to smoothly and quickly adapt the size of the staff to fluctuations in the number of patients”. Zuckerman, Hadley and Iezzoni (1994) also employed occupancy rate in their analysis of U.S. hospitals. However, they theorised and found that occupancy rates are inversely related to inefficiency. Finally, in a third approach to the question of capacity, Fazel and Nunnikhoven (1992) argued that the use of different categories of beds would highlight substantial cost structure differences between, say, ‘skilled nursing’ and ‘intermediate nursing’ care. In common with Kooreman (1994), they observed a negative relationship between size and efficiency.

Secondly, a number of studies have attempted to incorporate a measure of ‘quality’ or ‘specialisation’ as an explanatory factor in healthcare efficiency (Fazel and Nunnikhoven 1992; Chillingirian 1993). For example, Fazel and Nunnikhoven (1992) argued that an increase in the quality of healthcare is likely to require additional input units per unit of output, thereby implying lower relative efficiency for higher quality providers. In a related approach, Chillingirian (1993: 170) linked ‘quality’ in healthcare with ‘specialisation’ and presented evidence that health providers that are more specialised have been associated with a less efficient use of input resources. However, this evidence was not conclusive, since there was no significant relationship between the level of specialisation and the level of technical efficiency. Interestingly, Grosskopf and Valdmanis (1987: 93) argued that:

[P]ublic hospitals may actually ‘minimise’ quality because it is difficult to quantify when appealing for budget increases to the legislature ... or to city or county government. ‘Visible’ outputs and inputs are emphasised in this budgetary process, which may result in less costly, relatively low ‘quality’ health care.

Thirdly, a number of studies have attempted to incorporate issues of market structure and funding into the determinants of inefficiency. For example, the primary aim of Chillingirian’s (1993) analysis of U.S. physicians was to determine if prepaid group practices provided an incentive to use resources more efficiently, compared with more traditional types of practice settings (ie. fee-for-service). The evidence indicated that this was the case. By contrast, Fazel

and Nunnikhoven (1992) and later Rosenman *et al.* (1997) and Burgess and Wilson (1998) incorporated Herfindahl indexes of market concentration to evaluate the impact of increased competition on industry efficiency. Support for the hypothesised positive relationship in these studies was not forthcoming. Finally, a number of studies have employed the second-stage regression approach in order to proxy the effect of nondiscretionary inputs on healthcare efficiency, in particular geographic location. Zuckerman, Hadley and Iezzoni (1994) and Hofler and Rungeling (1994) established efficiency differences between urban and rural hospitals. In sum, the evidence found generally supports the proposition that imposed environmental factors affect the ability of healthcare organisations to attain efficient outcomes, be they hospitals, nursing homes, or even physician's practices.

CONCLUSION

In contrast to the widespread acceptance of econometric and mathematical frontier estimation techniques in financial services, the adoption of these same methods in healthcare contexts is still in its infancy. Some critics hold that the generic problems of omitted outputs, unmeasured inputs, and the imposition of strong and non-testable assumptions means that is “doubtful that the regulator can recover ‘true’ or efficient cost or production parameters from observed data with any degree of precision [moreover] even if one could recover them, they probably would have changed a few years later given the pace of change in this industry” (Newhouse 1994: 321). Still others argue that there has been substantial misuse of frontier techniques in health services. For example, one of the reasons for the rather icy reception for frontier efficiency techniques, particularly in public hospitals, may be that many studies have employed them to make direct policy recommendations regarding budget controls and cuts [see, for example, Zuckerman, Hadley and Iezzoni (1994) and Hadley and Zuckerman (1994)]. Policy recommendations such as these are, however, not universally held. Kooreman (1994), for instance, argues that it is conceivable that the appropriate action may not to be to cut the budget, rather to replace management. This particularly would be the case where cutting budgets may “result in a situation which is in conflict with government standards for the minimum capacity and quality of healthcare in a particular region” (Kooreman 1994: 346). Other policy recommendations made on the basis of efficiency measures have also included using them as a marketing tool to attract contracts and factors to incorporate into pricing models.

Notwithstanding these policy-related arguments, a number of empirical uncertainties are also found in the literature. For instance, despite the fact that early studies emphasised that the arguments in the first stage of a two-stage regression analysis must be completely distinguishable from those in the second, and that the second-stage should be treated as a truncated regression, lapses in thoughtful modelling are common in healthcare applications (Dor 1994: 331). Thus, while factors affecting inefficiency are now the focus of empirical research in other services, it is argued that healthcare research in the future should place more emphasis on carefully specifying the frontier. Moreover there is merit in the suggestion that technical problems such as zero inputs and outputs at certain hospitals and whether outputs are homogeneous and exogenous, do complicate this matter. However, it is unlikely that the health industry forms a sufficiently different case to isolate it from the substantial advances made in equally complex empirical contexts such as financial services and education.

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Table 1. Applications in healthcare services

Author(s)	Methodology ^a	Sample ^b	Inputs, outputs, explanatory variables (if applicable) ^c	Analytical technique	Main findings
Banker, Conrad and Strauss (1986)	DEA	114 North Carolina hospitals, 1978.	Nursing, ancillary, administrative and general services expenditure, capital expenditure. Patient days for inpatients less than 14 years, patient days for inpatients between 14 and 65 years, patient days for inpatients aged above 65 years.	Comparison of returns-to-scale, marginal rates of transformation and technical efficiency.	DEA identifies a richer and more diverse set of behaviour than non-frontier techniques.
Grosskopf and Valdmanis (1987)	DEA	66 Californian hospitals, 1982.	Number of physicians, full-time equivalent non-physician labour, admissions, plant and equipment assets. Acute and intensive care inpatient days, number of inpatient and outpatient surgeries, number of ambulatory and emergency care visits.	Descriptive analysis across public and not-for-profit hospitals.	Public hospitals have lower costs than not-for-profit hospitals.
Wagstaff (1989)	DFA and SFA	49 Spanish hospitals, 1977-1981.	Total costs (excluding capital expenditure), Six casemix categories (internal medicine, general surgery, gynaecology, paediatrics, intensive care, and other) as indexes, stock of beds, caseflow, dummy variable for teaching status.	Interpretation of parameter estimates.	Mean level of efficiency highly dependent upon approach employed.
Ley (1991)	DEA	139 Spanish hospitals, 1984.	Number of doctors, technical degree and other personnel, purchases of sanitary supplies and number of beds. Patient days, discharges because of recovery (medicine, surgery, obstetrics, paediatrics and intensive care), patient days in other wards (psychiatry, tuberculosis, long-term), number of emergency cases, operations and new-borns.	Descriptive analysis.	Private hospitals more efficient than public, no difference in efficiency between teaching and non-teaching hospitals.
Fizel and Nunnikhoven (1992)	DEA	167 Michigan nursing homes, 1987.	Registered nurse hours, licensed practical nurse hours, aides and orderlies hours. Skilled and intermediate-care. Percentage of skilled beds, number of empty beds, assessed penalty points, Medicare patients and beds, Herfindahl index of market concentration, dummy variables for urban and profit and not-for-profit homes.	Descriptive statistics across disaggregated sample. Second-stage least squares regression.	Second-stage regression analysis purges efficiency indices of 'confounding' factors. For-profit homes are more efficient than not-for-profit ones.
Valdmanis (1992)	DEA	41 Michigan hospitals, 1982.	Number of attendings, housestaff, physicians, nurses, other full-time equivalent staff, admissions, beds, net plant assets. Adult, paediatric, elderly, acute, intensive care inpatient days, number of surgeries, number of emergency care and ambulatory visits, total housestaff.	Descriptive analysis across public and private not-for-profit hospitals.	Public hospitals more efficient than non-profit hospitals. Alterations in input-output model bring differences in efficiency levels and ranks.
Byrnes and Valdmanis (1993)	DEA	123 Californian hospitals, 1983.	Number of registered nurses, management and administrative personnel, number of technical services personnel, aides and orderlies, licensed practising nurses, price of labour (reported wage rate), capital (average staffed beds), price of capital (depreciation divided by number of beds). Medical-surgical acute, medical-surgical intensive, and maternity discharges.	Descriptive analysis.	Advance on previous studies by incorporating price measures as well as physical unit measures.

Author(s)	Methodology ^a	Sample ^b	Inputs, outputs, explanatory variables (if applicable) ^c	Analytical technique	Main findings
Chillingerian (1993)	DEA	36 U.S. physicians, 1987.	Average length of stay, total ancillary services. Number of low-severity and high-severity cases. Average age of patients, area of specialisation, average severity, relative weight of caseload, physician's age, fraction of caseload with satisfactory outcomes, local or pre-paid practice membership.	Comparison of DEA with ratio analysis, slack analysis, Mann-Whitney tests, second-stage logit regression.	Key factors that influence physician efficiency include pre-paid group practices vs. fee-for-service payment structure.
Fare, Grosskopf, Lindgren and Roos (1993)	MI	17 Swedish hospitals, 1970-1985.	Real labour input (average labour expenditure per hour), real non-labour input (food, drugs, medical supplies and laundry excluding capital costs). Short-term inpatient care (proxied by discharges), long-term chronic care (proxied by bed days), ambulatory care (proxied by doctor visits).	Descriptive analysis of relative efficiency over time.	Advantages of approach over Tornqvist, Paasche and Laspeyres index-type productivity measures.
Hofler and Rungeling (1994)	SFA	1,079 U.S. nursing homes, 1985.	Total variable costs, nursing staff hourly wages, hourly wage for physicians and other professional staff, hourly wage for all other staff, capital (as proxied by number of beds). Skilled inpatient days, intermediate care inpatient days, other inpatient days. Type of home certification, physician availability, nursing staff characteristics, geographic region, chain membership, ownership type and hospital affiliation.	Second-stage OLS regression. Interpretation of parameter estimates.	Nursing homes appear to be cost efficient.
Kooreman (1994)	DEA	320 Dutch nursing homes, 1989.	Number of medical doctors, nurses, nurse trainees, therapists, general and other staff. Number of full and day-care, physical disability, and psycho-disability patients. Number of beds, occupancy rate, proportion of patients older than 85 years, length of stay, hospital affiliation, regional dummies, religious affiliation, dummy variable for patients' council.	Descriptive statistics, second-stage probit and tobit regressions.	A number of quality indicators have a negative effect on efficiency. Practical usefulness of DEA limited by the availability of data.
Zuckerman, Hadley and Iezzoni (1994)	SFA	4,149 U.S. hospitals, 1986/87.	Total costs, average annual salary per full-time equivalent employee, depreciation and interest expenses per bed. Post-admission inpatient days, post-admission inpatients days, outpatient visits. Percentage of beds in intensive care, non-surgery outpatient visits, long-term admissions, ratio of births to admissions, average casemix, inpatient surgical operations per admission, index of high technology services, ratio of residents to beds, accreditation indicator, individual Medicare-specific variables.	Correlation coefficients between alternative model specifications, inefficiency estimates from pooled and partitioned hospital groups.	Inefficiency measures generated insensitive to functional form. Large number of hospital outputs may not be treated exogenously nor homogeneously.
Chattopadhyay and Ray (1996)	DEA	140 U.S. nursing homes, 1982/93	Labour hours for dietary, housekeeping, laundry, director, registered nurse, licensed practical nurse and nurses aides staff, total expenditure on non-labour inputs. Medicare, Medicaid, private and other patient days.	Descriptive analysis.	For-profit home more efficient than not-for-profit homes.
Lo, Shih and Chen (1996)	DEA	82 Taiwanese hospitals, 1982.	Number of doctors, nurses, other staff and beds. Number of visits, operations and patient days, and average patient days. Dummy variables for public, military, corporate, religious and university hospitals, hospital size, percentage of patients over 65 years, percentage of beds in city, dummy variable for scanning equipment.	Descriptive analysis, second-stage tobit regression.	Public hospitals less efficient than private hospitals.

Author(s)	Methodology ^a	Sample ^b	Inputs, outputs, explanatory variables (if applicable) ^c	Analytical technique	Main findings
Luoma, Järviö, Suoniemi and Hjerppe (1996)	DEA	220 Finnish health centres, 1991.	Total operating costs (excluding rehabilitation), cost of purchased services, cost adjustment for remote areas. Health care and medical visits to a physician, health care or medical care visits to other personnel, supervised domiciliary care visits, dental care visits, special examinations, short-term inpatients days, long-term inpatient days for heavy and non-heavy dependence categories. Percentage of state subsidy, local government taxation per patients, distance to nearest hospital, proportion of population over 65 years, number of personnel posts, dummy variable for single-municipality health centre.	Descriptive analysis, second-stage Tobit regression.	Inefficiency linked to larger state subsidies and higher per capita taxable income, remote centres more inefficiency. Efficiency also linked to increases in proportion of elderly in area.
Gonzalez Lopez-Valcarcel and Barber Perez (1996)	DEA and SFA	75 Spanish hospitals 1991-1993.	Number of doctors, other staff and beds, total costs for cost frontier. Medical, surgical, intensive care, obstetric and new-born inpatient days, number of ambulatory surgical procedures, operations with hospitalisation and total admissions, index of ambulatory/emergency visit and high-tech activity. Percentage of doctors on staff, percentage of sub-contracted work, rate of hospital admission per 1000 population, dummy variables for regions.	Descriptive analysis, second-stage Tobit regression.	Differences in efficiency associated with size, the extent of sub-contracting and the rate of capacity utilisation.
Magnussen (1996)	DEA	46 Norwegian hospitals, 1989-1991.	Number of physicians and other personnel, number of beds. Medical, surgical, simple and complex patient days, number of medical and surgical patients, number of long-term care days and outpatient visits.	Descriptive analysis.	Difficulty in identifying high, medium and low performers using DEA.
Thanassoulis, Boussofiene and Dyson (1996)	DEA	189 U.K district health authorities, 1985/86.	Numbers of obstetrics/gynaecology staff, paediatricians, midwives and nurses, general practitioner's fees. Number of deliveries, deliveries to resident mothers, babies less than 1500g birthright and legally induced abortions, length of stay.	Descriptive analysis, correlation between efficiency indexes and performance indicators.	DEA and performance indicators weakly agree on unit performance. DEA as a tool for target setting.
Defelice and Bradford (1997)	SFA	924 U.S. physicians, 1984/95.	Number of physician visits. Weekly hours of medicine practice by physician, nursing and clerical time per physician, percentage of visits using lab tests or x-rays. Years of physician experience, percentage of physicians earning in excess of \$10,000 exogenous income, percentage of physicians in general or family practice, percentage of physicians working in internal medicine, paediatrics or partnerships, number of physicians in practice, percentage of physicians sharing net revenue equally and multi-speciality groups. Number of board-certified physicians in speciality in county, number of HMOs and hospitals in country, number of physicians per 1000 county population, percentage of patients insured by Medicaid, percentage of visits provided by hospital, number of offices with lab or x-ray equipment, level of malpractice premiums.	Descriptive analysis, single-stage least squares regression.	No difference in efficiency between group and solo practices.
Parkin and Hollingsworth (1997)	DEA	75 Scottish hospitals, 1991-94.	Number of staffed beds, total number of trained and learning nurses, total professional, technical, administrative and clerical staff, total non-nursing medical and dental staff, cost of drug supply, NHS capital charge on capital assets and investments. Medical and surgical discharges, accident and emergency attendance, outpatient attendance, obstetrics and gynaecological discharges, other speciality discharges.	Efficiency scores across different combinations of inputs-outputs and time.	Large amount of difference in efficiency results depending upon specification.

Author(s)	Methodology ^a	Sample ^b	Inputs, outputs, explanatory variables (if applicable) ^c	Analytical technique	Main findings
Rosenman, Siddharthan and Ahern (1997)	DEA	28 Florida health maintenance organisations, 1994.	Total administrative expenses, total assets, total medical expenses. All enrollees, Medicare enrollees, Medicaid enrollees. Plan size (total enrolment), Herfindahl index of enrolment concentration (Commercial, Medicare and Medicaid enrollees).	Descriptive analysis, second-stage OLS regressions.	Efficiency is equal across organisational and ownership. HMOs that accept Medicaid patients are more efficiency.
Chirikos (1998)	SFA	186 U.S. hospitals, 1982–1993.	Total operating expenses. Number of post-admission patient days with Medicare, Medicaid or other as primary payer, case weighted admission index, case-equivalent outpatient index (ratio of gross outpatient revenue to gross inpatient revenue) emergency room outpatient index (ratio of gross ambulatory revenue to gross emergency services revenue). Wage rates of three categories of personnel (inpatient and ambulatory, ancillary, and administrative), ratio of depreciation to book value of plant and equipment, ratio of interest charges to current assets. Cost per case, annual cases, control of ownership status (government, proprietary or voluntary), licensed beds, teaching status, market share, population density, and physicians per 100,000 persons.	Descriptive analysis across explanatory variables.	Empirical results sensitive to specification of outputs, factor prices or other covariate models. Government-controlled hospitals more efficient, less-efficient hospitals in highly competitive, population- and physician-dense areas.
Linna (1998)	SFA and MI, DEA.	43 Finnish acute care hospitals, 1988–94.	Net operating costs, total number of beds, average hourly wage rate, annual price index for local government health care expenditure. Total number of emergency visits, total scheduled and follow-up visits, weighted number of total admissions, total bed days, number of residents receiving training, number of on-the-job nurse training weeks, impact weighted scientific publications. Dummy variables for teaching status, readmission rate for admissions, year dummies.	Descriptive analysis, rank correlation between efficiency scores, single-stage SFA incorporating efficiency effects.	Choice of modelling approach does not affect results. SFA and DEA models revealed productivity growth over period to be the result of exogenous technical change.
Puig-Junoy (1998)	DEA	993 Spanish patients in 16 intensive care units (ICU), 1991/92.	Patient survival probability at admission, mortality risk level, weighted ICU days, non-ICU days, available nurse and physician days per patient, technological availability Number of surviving days in hospital, surviving discharge status. Dummy variable for for-profit hospitals, Herfindahl competition index, number of beds in ICU, proportion of patients in same risk group, number of inpatient days for ICUs using clinical guidelines and nurse/physician evaluation program, number of daily visits, dummy variable for teaching hospital, mortality risk score, age, dummy variables for respiratory failure, cardiovascular disease, trauma, urgent admission, postoperative patients with programmed admission,	Descriptive analysis, second-stage log-linear regression.	Higher risk patients managed less efficiently than lower risk patients, higher technical efficiency in for-profit teaching hospitals, and those with nurse and physician program evaluation. Diagnostic variable generally unrelated.

Author(s)	Methodology ^a	Sample ^b	Inputs, outputs, explanatory variables (if applicable) ^c	Analytical technique	Main findings
Burgess and Wilson (1998)	DEA	1,545 U.S. hospitals, 1985-88.	Number of acute-care beds, long-term hospital beds, registered nurses, practical nurses, other clinical and non-clinical labour, Acute care inpatient days, case-mix adjusted acute care inpatient discharges, long-term care inpatient days, outpatient visits, ambulatory surgical procedures, inpatient surgical procedures. Dummy variables for state/local government, non-profit, for-profit, Veterans Affairs and teaching hospitals, Herfindahl index of county competition, average length of stay, percentage of registered nurses, ratio of clinical to non-clinical staff, administration cost per bed day.	Descriptive analysis, second-stage least squares regression.	No difference in efficiency across different ownership structures or in teaching hospitals. Greater expenditures on administration and nursing staff associated with higher efficiency.
Notes: (a) DEA – Data Envelopment Analysis, SFA – Stochastic Frontier Analysis, DFA – Deterministic Frontier Analysis, MI – Malmquist Indices; (b) Singular dates represent calendar or financial year cross-sections, intervals represent time-series; (c) In order by paragraph.					

